Citation: Kush, John S., comp. 1999. Longleaf Pine: A Forward Look, proceedings of the second Longleaf Alliance conference; 1998 November 17-19: Charleston, SC. Longleaf Alliance Report No. 4.

Diameter distributions of longleaf pine plantations - a neural network approach

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ABSTRACT: The distribution of trees into diameter classes in longleaf pine (*Pinus palustris* Mill.) plantations does not tend to produce the smooth distributions common to other southern pines. While these distributions are sometimes unimodal, they are frequently bi- or even tri-modal and for this reason may not be easily modeled with traditional diameter distribution models like the Weibull whose form is unimodal and monotonic. Neural networks, a development of artificial intelligence research, can take on any form that is found in the data, allowing the prediction of many phenomena without the assumption of a given model form. To see if this new technique has merit in forest modeling, the diameter distributions of several longleaf pine stands were modeled using a neural network process. Weibull distribution models were also fit to the data using regression and parameter recovery techniques. These approaches were then compared. The neural network procedure appeared to provide slightly better predictions than either of the traditional methods. Results of this comparison are presented in this poster. This early result indicates that this new technique is promising and deserves further investigation.

INTRODUCTION

The three parameter Weibull probability distribution function (Weibull 1951) can take on a wide variety of shapes, and has been found to be an applicable model for approximating tree dbh distributions (Bailey and Dell 1973). Because of this plasticity, many stand-level diameter-distribution growth and yield models in use today rely on the Weibull probability distribution function (Matney and Sullivan 1982; Bailey and Aleixo da Silva 1988; and Zarnoch, et al. 1991). However, the Weibull distribution does not span the entire function space and it's performance as a dbh distribution estimator varies widely between data sets. In some dbh distribution modeling cases, the Weibull tends to produce poor estimates in the tails. In other situations, the Weibull may lock the tails down and overcompensate by missing badly in the middle part of the distribution. As any error in the middle and upper dbh ranges of a distribution can have a large impact on derived volume estimates, growth and yield models constructed from the estimates will produce biased volume estimates. Generally applicable thus does not mean that the procedure is always best,' as growth and yield modelers are constantly searching for procedures to improve dbh distribution estimates. Artificial neural networks hold a future promise of being able to provide better estimates of dbh distributions that do not rely on assuming an imperfect underlying probability model.

In general, artificial neural networks are appropriate in modeling situations where: (1) the application is data intensive and dependent on multiple interacting parameters; (2) the problem area is rich in historical data or examples; (3) the available data is incomplete, contains errors, and describes specific examples, and (4) when the function to determine solutions is unknown or expensive to discover (Bailey and Thompson 1990). All these conditions are to some degree met by the typical growth and yield data base. The results from neural network research relevant to their use for approximating dbh distribution are theorems by Cybenko (1989), Sun and Cheney (1992), and Light (1992). These theorems show that a single output, two-layer feedforward network employing continuous sigmoid and other more general activation functions with a sufficient number of hidden units, can approximate any continuous function to any desired accuracy. Some researchers (e.g., Josin 1987) point to Kolmogorov's (1957) theorem on the realization of real-valued functions as strong, but not conclusive, evidence that neural network models can learn to approximate any continuous real-valued multivariate function, while minimizing error in the least-mean-square sense, based only on an example mapping.

Given the advertised great promise of neural methodology, the authors decided that mounting a preliminary investigative benchmark comparison of this technique with the traditional methods of diameter distribution modeling was warranted. The network model selected for this comparison is a simple fully-connected feedforward back-propagation delta learning rule network; and the two traditional Weibull probability function based benchmark test models selected were a diameter moment parameter recovery system and a direct parameter prediction model. Each of these techniques was then applied to predicting the diameter distributions of three distinctly different unthinned planted longleaf pine databases from stands originating under three different conditions. If these preliminary results positively favored the neural network, additional work would be undertaken to refine the unthinned stand model and construct network models for predicting thinned stand diameter distributions.

The analysis of the multitude of statistical criteria selected for the preliminary benchmark testing of the neural network model is repotted in this paper.

RESULTS AND DISCUSSION

The first comparison of note is a graphical examination of the performance of the various diameter distribution recovery methods. In many cases there was little difference between the accuracy of the distributions predicted by the Weibull distributions and the neural network, but in distributions that were multimodal the neural networks were clearly superior even when they were not ideal.

Visually superior fits were often also better when evaluated using mathematical goodness-of-fit methods. When mean square error, fit index, generalized R^2 (Anderson-Sprecher 1994), comparisons of percentages of 'trees in different size classes, χ^2, Kolmogorov-Smimov statistic, and distribution means were used to compare the predicted distributions, the neural network was most often best.

Another graphical comparison made was an examination of maximum absolute errors, average absolute errors, and average bias across diameter classes. All of the methods had the greatest maximum absolute error in the lower diameter classes and tended to be negatively biased. It is only in looking at average bias that the neural network method shows its superiority. While the bias trends 'are similar across all methodologies, the magnitude of the bias is much less in the lower diameter classes for the neural network.

These results show that neural networks can perform at least as well as traditional methods and often better. They may be reducible to nonlinear models (Sarle 1994), but their strength lies in that the form of the model does not have to be specified In advance. This is a great advantage, because, in spite of many efforts in process modeling, we still do not understand the processes of growth that would allow us to create models that are not tled to empirical data. Even the Weibull function has no biological meaning. It is simply a mathematically handy function with the ability to assume a variety of appropriate shapes (Weibull 1951).

There are two principal weaknesses in neural networks as used in this poster. The first is that, although a model does not have to be specified, the number of hidden nodes and layers and the transfer function to be used still must be determined. A correct choice of options can make a great difference in the success of the modeling effort. Also, there are many rules of thumb for selecting these variables, but it really comes down to a matter of trial and error. Secondly, the network that results from a training program is a black box. In this case, it is implemented as a C or FORTRAN program, but an examination of this program reveals so many interacting equations that clear relationships are hard to determine. Fortunately, this latter difficulty is easily alleviated through the use of sensitivity analysis (Klimasauskas 1991).

A sensitivity analysis was conducted on the input parameters of age, height of dominant trees, and number of trees per acre to see what effect changes in these parameters would have upon stand basal area, arithmetic mean dbh, and quadratic mean dbh. All of the methods are very similar in their sensitivity to input, with only the age influence on basal area showing a change that exceeded the change in input. Also it can be seen that trees per acre has a moderate influence and the height of dominant trees has almost none. These results are rather similar across all of the site types with old field sites being the least sensitive and prepared sites the most.

CONCLUSION

This paper clearly demonstrates that artificial neural networks are an excellent alternative to the traditional method of predicting unthinned stand diameter distributions with estimated Weibull probability functions. The superiority of the neural network for the data sets in this study arises because the Weibull is not the correct model for the data. On other data sets when the Weibull distribution fits the data better, the neural network and Weibull probability distribution approaches will perform equally well. The clear advantage of the neural network over the parametric function modeling techniques is that in almost all cases a neural network solution will minimize the root mean square error. If the Weibull distribution or other assumed probability function does not fit the data, the modeler is left with the very difficult task of piecing together and/or finding a new parametric model form for the problem.

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